The Use of Smartphone Apps as a Weight Loss Intervention

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Abstract

Today, over two-thirds of American adults are obese and this trend shows no signs of changing. Because older methods have been ineffective in decreasing this epidemic, this literature review was carried out to examine smartphone apps, a new technology that has recently become ubiquitous. Smartphone apps offer a novel approach to gather real-time patient health data and create personalized interventions to increase physical activity and maintain a healthy diet. In order to explore the evidence for apps as a weight-loss tool, a systematic search for studies that had smartphone apps as a patient intervention for weight loss was conducted on December 19th, 2013. The studies were reviewed for evidence of apps' effectiveness, usability, and use of theory. Overall, there was a general lack of theory used in the creation of smartphone apps, and most studies had small sample sizes and lack of controls. The results of this review point toward smartphone apps being a usable, effective, and inexpensive intervention for patent weight loss. Because of the studies' limitations, this conclusion must be qualified, and further research needs to be conducted in order to solidify these results.

Keywords: Smartphone, Apps, M-health, mobile, obesity, weight loss, stress reduction, diet, exercise, physical activity, patient intervention

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Background

According to the Centers for Disease Control and Prevention (CDC), one-third of adults in the United States are obese, and their medical costs are an average of $1,429 higher than those of normal weight adults ("Overweight and obesity," 2013). The proportion of adults who are obese increased dramatically from 2000 to 2010. Although no state had an obesity prevalence of 30% in 2000, by 2010, obesity rates in 12 states were greater than 30% ("Overweight and obesity," 2013). Furthermore, more than two-thirds of adults are either overweight or obese (Ogden, Carroll, Kit, & Flegal, 2014). Although rates may have stabilized over the past decade, they are not improving and remain unacceptably high.

With this stasis in mind, it is critical that we admit that the older methods upon which we have relied—pamphlets, diet and exercise plans, and in-person patient-provider sessions—may need to be reexamined, and perhaps supplemented with the new technology available today. One such technology that could help effectively combat obesity is the smartphone, and particularly, the smartphone app. A smartphone is a mobile phone that has a large screen, sensors, and an operating system that is capable of running applications or “apps,” which are pieces of software that serve various functions ("Smartphone," 2014). These smartphones, and the apps that run on them, have various advantages that past interventions lack (in whole or in part), including their ability to continuously record and provide instantaneous tailored feedback on health data, their high degree of penetration in the United States, and the ease with which they can be integrated into one’s life.

Continuous Recording and Tailored Feedback

Smartphones can continuously record user data and utilize that information to create personalized interventions. Historically, interventions have been based on discrete data points such as questionnaires, observations, and interviews. These data were used to create a patient profile, and using that profile, interventions could be implemented that were patient-specific. The inherent problem in these methods is that the data is discontinuous and the points at which they are taken can be separated by large spans of time. Without a cost-effective alternative, these snapshots were the closest thing to a full picture of the patient that a provider could hope to achieve (Spring, Gotsis, Paiva, & Spruijt-Metz, 2013). The limits created by this disjointedness are clear, but this can now be traversed with the advent of smartphones. They are capable of constantly monitoring physical location, movements, and even social interactions, and the resulting data can then be synthesized to predict psychophysiological states and behavior patterns. This data can in turn be met with immediate personalized interventions (Riley et al., 2011). A prediction by Spring perfectly exemplifies this:

> [If] your phone or fitness device let[s] us know that you are entering a fast food restaurant, we can make this time-and-location- stamped data quickly available for analysis on a smartphone, the cloud, or a back-end secure server. That enables us to apply the method of ecological momentary assessment, whereby your smartphone "pings" you to ask if you are hungry or stressed, or what you plan on buying. Through this combination of technologies and methods, we can begin to form a rich and detailed picture of how your feelings, thoughts, and behaviors affect each other that is accurately placed in time, and in social- and built-environmental context" (Spring et al., 2013, p. 36).

Privacy issues aside, the high degree to which a smartphone can be adapted to learn about its user and interact with its environment allows for tailored interventions that could never before have been imagined.

Penetration

Smartphones are becoming ubiquitous, and a recent report released by comScore, an organization that tracks data usage trends, showed that 149.2 million Americans, 62% of the population, owned smartphones (Lella, 2013). Counter to intuition, this reach extends further among non-white than the more affluent white population. A report by the Pew Research Center put the total number of American adults who own a cell phone at 58%, with a further break down of 53% of Whites, 59% of African Americans, and 61% of Hispanics ("Mobile technology fact sheet," 2014). This is important considering the higher rates of obesity fall with Non-Hispanic blacks (49.5%) and Hispanics (39.1%) as compared with non-Hispanic whites (34.3%) ("Overweight and obesity," 2013).

Integration

Many Americans not only own the technology, but also carry it with them wherever they go. Easily forgotten activities like putting on a pedometer, or documenting what is eaten and how much one has exercised, can be automated, or at the very least, made less obtrusive and easier to incorporate into the average patient's life. One example of this is calorie counting, a tedious task that can be made easier using a smartphone's camera, which has the capability to scan a QR code, automatically connect to a food database, and record an entry in a food diary (Pagoto, Schneider, Jojic, Debiasse, & Mann, 2013).

Why Research and Why Theory

"Healthcare apps" have been around for a few years now, with popular diet and weight loss apps, such as Calorie Counter by MyFitnessPal, having over 500,000 downloads. Even with this proliferation, and all of the potential benefits, there has been little research on the effectiveness or usability of apps and whether they have a significant impact on patient weight loss. Prior systematic reviews of weight loss apps focused on neither effectiveness nor usability, and instead focused on the approaches and theoretical foundations of commercial apps. Reviewers found that few apps are based on theory, and those that are based on theory are often downloaded less frequently than those that are not (Azar et al., 2013; Cowan et al., 2013; West et al., 2012).

This absence of theory is a problem not only because developers are failing to build on prior research, but also because it makes it much more difficult to replicate a given app's effectiveness. The diversity of apps makes their classification difficult, and without theories to guide their creation and help categorize them, discovering what is effective and what is not effective is hampered and improvement is stalled. Therefore, in addition to examining the usability and effectiveness of smartphone apps geared toward weight loss, this review attempts to classify them according to the theories upon which they are built and the behaviors they target in an attempt to understand what makes them usable and effective. Summed up, the questions that guide this inquiry are: (1) What theories are being used in the development of weight loss apps, (2) What behaviors are being targeted, (3) Are these apps considered usable by the studies' participants, (4) Are these apps effective in helping decrease weight or change patient behavior, and (5) Is there a correlation between effectiveness or usability and either the theory used or the targeted behavior?

Methods

PsychINFO, PubMed, and Scopus, were searched on December 19th, 2013 for reports from empirical studies that examined smartphone apps as a patient intervention for weight loss. The following search string was used for all three databases: (phone OR mobile) AND ((app) OR (apps) OR (application*)) AND ((physical activity) OR (exercise) OR (diet) OR (weight loss)) AND ((Intervention*) OR (support*)). Articles not published within the last five years were excluded because of the rapid evolution of smartphone technology. Because terms like “mhealth” and “telehealth” are not a fully established part of the research vernacular, the search terms “phone” and “mobile” were used instead, which increased results. In order to restrict mobile and phone interventions to those focused on smartphone apps, the search terms “app,” and derivatives such as “application,” were used.

Because this review is focused on smartphone apps, articles that had Short Message Service (SMS) texting as their only intervention were removed. In addition, articles that were not in some way related to activities that helped prevent obesity, such as diet, exercise, or physical activity, were also removed. For example, one excluded study looked solely at how apps can be used to help people with diabetes control their blood sugar level (Rollo, Ash, Lyons-Wall, & Russell, 2011).

Using the search terms, 473 articles were found, and by reading their bibliographies, 37 more articles were added. This total number dropped to 357 after removal of duplicates. These abstracts were read, and those that did not match the criteria were removed, further decreasing the total potential studies to 76. Finally, the remaining articles were read in-depth and 17 were found to match the review’s criteria, which is outlined by Figure 1. Those that met the review’s criteria were then mined for data, and three separate tables were created. The first table consisted of general features of the study, the second table was dedicated to findings on usability, and the third table was dedicated to findings on effectiveness.

Table 1 consists of 9 columns, which include: (1) The first author's name and date, (2) The name of the mobile app(s) used, (3) The key distinguishing features of the mobile app, (4) Any additional intervention(s) given in addition to the mobile app, (5) The comparison groups, (6) Behaviors targeted (diet, physical activity, or stress reduction), (7) One of three theory classifications (analytic, social or affective), (8) Any cited theories used in the creation of the app, and (9) The sample size used in the study.

For column 7, "Theory Type," applications were coded based on the motivations targeted by the app using a classification system developed by King et al. (2013). Applications were coded as: (1) "Analytic" apps that rely on theories such as social cognitive theory and regulatory principles of behavior change, which motivate change by providing data, tips, and feedback to the user, (2) "Social" apps based on social influence theory and perspectives, which motivate using the pressures created by social interactions and norms, and (3) "Affective" apps, based on theories like operant conditioning and emotional transference, which motivate using techniques like positive reinforcement and "rewards" to influence mood and emotion (King et al., 2013).

Table 2 focuses on indicators of usability of the study's apps. Study findings were categorized into four columns: (1) "Use of App," (2) "Satisfaction," (3) "Ease of Use," and (4) "Convenience of Use." "Use of App" refers to how often the app was used during the intervention period, which includes daily or weekly frequency or total number of app transmissions. "Satisfaction" refers to how satisfied the participants were with using the app, which included how likely participants would be to use it in the future, how much they liked the app, or how likely they were to recommend the app to a friend. "Ease of Use" refers to users' perceptions of how easy it was to learn how to work the app. Finally, "Convenience of Use" refers to how quickly the user could access the app, input data, and its overall usability.

Table 3 was dedicated to indicators of intervention effectiveness and categorized into two columns: (1) "Change in Weight" and (2) "Change in Behavior." For "Change in Weight," anything related to a decrease in weight (e.g., BMI, waist circumference, weight loss) was recorded. For "Change in Behavior," any changes in behavior that lead to decreases in weight, such as exercising more often, regular eating, decreasing stress, or less "discretionary time" spent sitting were recorded.

Findings

In total, 17 studies reporting on 19 apps were included in the review. All 17 were quantitative studies, and 10 assessed effectiveness and 14 assessed usability. Out of the studies reviewed, five were conducted in the United States, two were conducted in the United Kingdom, one was conducted in Spain, one was conducted in Portugal, five were conducted in Australia, one was conducted in Korea, and two were conducted in Finland.

Theory

Only a minority of papers provided the theories that were used to ground their studies, as shown in Table 1. In fact, out of 17 studies, only 7 referenced any theory, with the theories referenced being: (1) Self-Regulation Theory, (2) Behavioral Science Theory, (3) Social Influence Theory, (4) Social Cognitive Theory, (5) Theory of Reasoned Action and (6) Theory of Planned Behavior. Only Theory of Planned Behavior (TPB) and Social Cognitive Theory (SCT) were referenced more than once, with the former being referenced twice and the latter three times.

Out of the 19 apps reviewed, 15 apps had features that fell within the “Analytic” category, 4 apps had features that fell within the “Social” category, and 5 had features that fell within the “Affective” category. Examples of “Analytic” apps included apps that could track caloric intake and energy expenditure and provide a graphical interface using this data, along with an app that adjusted health goals based off this input. Examples of “Social” apps included apps such as Twitter, which could share exercise and food intake for the day, along with an app that compared the user’s progress with that of group members with whom she was competing. Lastly, examples of “Affective” apps included an app that had an avatar that lost or gained weight based on the user’s weight and an app that “unlocked” trophies as the user achieved new milestones.

Behaviors Targeted

Of the 19 apps reviewed, 8 focused on increasing physical activity, 4 focused on healthy eating, 5 focused on a combination of physical activity and healthy eating, and 1 focused on decreasing stress. Eleven of the apps targeted increasing physical activity by creating a graphical interface, such as charts and graphs, which used exercise data input by the user, while one app did this automatically by pulling information from the phone’s built-in accelerometer. The diet interventions were more varied, with examples such as a regular food diary, a picture food diary that prompts the user with a picture of her previous meal with every new entry, and a “diet game” that helps users learn nutritional information. Additionally, two studies used Twitter to add a social component in which one could share her dieting results with friends.

Usability Studies

Of the 5 studies that assessed percent of participants who found their app convenient, in 4 greater than 50% of the sample agreed that the app was convenient to use. Of the 9 studies that assessed percent of participants who found their app easy to use, all 9 had over 50% of their sample agree that the app was easy to use. Of the 7 studies that assessed percent of participants who were satisfied with their app, 6 studies had over 50% of their sample satisfied with the app or would use it again. In only one study was the intervention app used significantly less than the comparison intervention, the Actigraph GT3X, which the researchers attributed to the comparison being a "gold standard," along with the patient's phone battery dying, resulting in lost data (Donaire-Gonzalez et al., 2013).

Of the 14 studies that tested for usability, sample sizes ranged from 10-352. Ten of the studies cited sample size or composition as a limitation, with 1 of the studies having only women in its sample, 1 having mostly university students in its sample, and 7 of the studies having a sample less than 100 (Brindal et al., 2013; Carter, Burley, Nykjaer, & Cade, 2013; Donaire-Gonzalez et al., 2013; Hebden et al., 2013; King et al., 2013; M. Kirwan, Duncan, Vandelanotte, & Mummery, 2013; Morwenna Kirwan, Duncan, Vandelanotte, & Mummery, 2012; Lee, Chae, Kim, Ho, & Choi, 2010; Mattila et al., 2013; Robinson et al., 2013). One study did not cite sample composition as a limitation, but its sample was composed only of university students (Rodrigues, Lopes, Silva, & Torre Ide, 2013). Four papers cited the short lengths of their study as a limitation, but three of these also studied effectiveness, so this may have not have been as important in terms of studying usability (King et al., 2013; Morwenna Kirwan et al., 2012; Lee et al., 2010; Robinson et al., 2013). Only 4 of the studies had a sample size greater than 50, a diverse population, and a comparison group (Carter et al., 2013; Hebden et al., 2013; Morwenna Kirwan et al., 2012; Mattila et al., 2013).

Effectiveness Studies

Of the seven studies that tested for a change in weight, three found a significant difference between those using the app and not using the app (Carter et al., 2013; Lee et al., 2010; Mattila et al., 2013). Two of the studies that did not find a significant effect on weight loss, however, still found that using the app favored weight loss (Brindal et al., 2013; Robinson et al., 2013). One study that did not find significant weight loss results discontinued meal replacements half-way through the study, which may have affected results, but the intervention group still had a significant increase in both motivation and positive affect as compared with the control group (Brindal et al., 2013). Another study that did not find a significant difference had as its comparison group a podcast intervention that was shown to be significant in an earlier study. The later study did not analyze the app as compared with a control or traditional methods, which may have yielded significant results (Turner-McGrievy & Tate, 2011).

Of the eight studies that tested for a change in behavior, four found a significant change in exercise when using the app as compared with the comparison group (Brindal et al., 2013; Fukuoka, Vittinghoff, Jong, & Haskell, 2010; King et al., 2013; Mattila et al., 2013). Out of the three that did not find a significant change in behavior, one did find that both the app and the control group had a non-significant increase in walking (Khalil & Abdallah, 2013). Of the five studies that examined diet, one had a significant decrease in caloric intake and one had a significant increase in participants' motivation to stick their diet (Brindal et al., 2013; Fukuoka et al., 2010). The one study that examined stress did not find a significant decrease in stress in participants who used the stress app (Mattila et al., 2013).

Of the 10 studies that tested for effectiveness, sample sizes ranged from 8-352. All 10 studies cited sample size or composition as a limitation, with 2 of the studies having only women in its sample, 2 having mostly women in its sample, 2 having mostly university students in its sample, and 8 of the studies having a sample of less than 100 (Brindal et al., 2013; Carter et al., 2013; Fukuoka et al., 2010; Hebden et al., 2013; Khalil & Abdallah, 2013; King et al., 2013; Lee et al., 2010; Mattila et al., 2013; Robinson et al., 2013; Turner-McGrievy & Tate, 2011). Six papers cited the short lengths of their study as a limitation (Fukuoka et al., 2010; Khalil & Abdallah, 2013; King et al., 2013; Lee et al., 2010; Robinson et al., 2013; Turner-McGrievy & Tate, 2011). After analyzing all of the studies, it was noted that no study had a sample size greater than 100, a diverse population, and a comparison group.

Barriers

Out of all of the studies, only five investigated what barriers may have prevented their intervention app from being successful (Ahtinen et al., 2009; Brindal et al., 2013; Hebden et al., 2013; Mattila et al., 2013; Robinson et al., 2013.) There were no common barriers cited by the reviewed articles, however, there were a few notable barriers that are worth exploring in future research. One barrier was social context, with the idea being that users may be hesitant to use a health app when in the company of others because of the negative stigma attached to being perceived as an “overeater” or “lazy” (Robinson et al., 2013). Another potential barrier given in reference to an app’s usability was the steep learning curve associated with either using a smartphone for the first time, or just learning how to use a new app (Brindal et al., 2013). This “technology literacy” barrier was also cited in a focus group conducted prior to designing an app, along with fear of failing, and a general lack of interest over time (Fukuoka, Kamitani, Bonnet, & Lindgren, 2011). Finally, an unexpected barrier cited by participants was becoming irritated by the pressure to do healthy activities created by the app’s notifications (Mattila et al., 2013).

Limitations

There were several limitations to this review. Only three search engines, PubMed, PsychINFO, and Scopus, were used to identify relevant studies, so papers not available to these search engines, along with unpublished papers, were not included. Moreover, only after the review was near completion did it become apparent that "stress management" should have been included in the original search terms. There was only one paper with this intervention, and the term "weight loss" should have picked up any studies that may have had stress reduction as an intervention, however it is not known if studies were overlooked because of this oversight.

Additionally, it was sometimes difficult to choose which papers to include because the interventions were not always well explained. There were a few factors that generated this uncertainty, including the use of multiple interventions, whether the study app was a secondary intervention, and ambiguity about whether an app or SMS texting was being used. A decision about whether to include a study was sometimes based on limited information; therefore there may have been unnecessary exclusions. Finally, the biggest limitation involved the lack of studies with large sample sizes, controls, and apps as their sole intervention.

Discussion

As noted earlier, because of the limited number of studies, none were excluded based on quality indicators such as small sample size or lack of a control group. Although a few of the studies had comparison groups such as a written diary or a website, only one of the studies had a "placebo" app to compare the effectiveness of the app they were studying with one they created that was not based on theory or research. Because of these issues, there were few studies that could stand up to scrutiny, but there was still evidence that favored these interventions being both accessible in terms of usability and effective in changing behaviors and leading to weight loss. The fact that half of the studies that looked at either weight loss or an increase in exercise had significant results lends support to this.

In relation to the lack of significance found by a few of the studies, one must ask whether it is because apps are truly not effective as an intervention, or whether the limitations were with the behavioral change approaches that the apps employed. That is, is the lack of significance due to the apps' behavioral targets and theoretical approaches? It is difficult to say whether an app that functions as an electronic diet journal fails to lead to significant behavior change because it is an app per se or because it targets diet and uses a Social Cognitive Theory approach. If it is true that apps have significantly different results based on the behavior they target, the way they target it, or the theory they rely on, do patterns of what is effective verses not effective emerge from the apps reviewed?

With this question in mind, the studies were reexamined for any patterns that might explain the difference in significance. Physical activity and diet were targeted with the same frequency, but there was no discernable difference in impact on weight loss or behavior. The result of the one study that had a stress reduction app was significant weight loss, but there was not a significant decrease in stress, and the stress reduction app was coupled with two other apps during the study period. Therefore, it cannot be said with certainty that this particular stress-focused app led to the study's results. In relation to theory, most of the studies did not incorporate or did not cite a theory used to create their apps. As mentioned, the few that did cite theory greatly varied, and only two theories (Social Cognitive Theory and Theory of Planned Behavior) were used more than once. The scarcity of large studies with controls, coupled with the inability to identify the theories used in each study, made it unfeasible to detect any relationship between significance and either behavioral target or theory used.

While the dearth of studies dedicated to this new technology is understandable, the reason why many of these apps are being developed and tested without any theoretical basis is more difficult to understand. Indeed, there is great reason to look to theory to ground these apps in theory. As King writes, “Applications of relevant behavioral theory and evidence can inform the selection and timing of intervention components, thereby increasing the potential effectiveness of smartphone-delivered programs” (King et al., 2013). Disturbingly, this failure is perhaps not an oversight on the researcher’s behalf, but a conflict that arises when the engineering science required in creating these apps supersedes the behavioral theories that we adhere to in public health. As Spring explains,

> The difference is that computational modeling is driven descriptively from the bottom up by the obtained data, consistent with methodological tradition in engineering science, rather than top down by a set of constructs and propositions that predicts a priori how the data should look, consistent with methodological tradition in behavioral science” (Spring et al., 2013, p. 37).

She also argues that behavioral concepts are too “fuzzily defined” for computer scientists, which has resulted in these concepts being avoided in the creation process altogether.

Although these concepts may be somewhat “fuzzy” and do not necessarily provide one “right answer,” there still exists a spectrum of better and worse interpretations. For example, if an app is developed using the Theory of Planned Behavior (TPB) and focuses on the tenet of subjective norms, or how an individual perceives the views and judgments of significant others, then it must create significant social pressure on the user for the intervention to be successful. It could attempt to do this by sharing the user’s diet results with a weight loss cohort she has only met once, or it could do this by sharing those same results with family and friends. Both interpretations are correct, however, the latter is more faithful to the TPB's tenet of subjective norms and arguably a better interpretation. A behavioral theory's lack of definite answers should not trump its potential benefits for researchers attempting to translate it into an app. These traditions must be bridged, whether that be by updating behavioral science theories to make them more dynamic, quantifiable, and responsive to technological data (as Spring suggests), or simply by making these concepts more concrete and interpretable. Until then, this lack of theory will not only be a waste of resources, but it will also continue to make it difficult to categorize and identify which apps result in the most significant results.

While there were several limitations, the data does provide the opportunity to make smaller claims. One claim is that apps can be developed that are not only cheaper, but can be as effective, if not more effective, than current interventions. As Table 3 shows, there are examples of app interventions that are as effective as current methods such as written diaries and more effective than methods such as websites. Remarkably, these apps were using only the most basic functions of what is possible given the degree to which healthcare apps can be tailored to an individual. Users can receive continuous feedback on how they are doing in relation to their goals, prompts that remind them to input their exercise or dietary intake for the day, and can even receive a recommendation on how much they should increase their walking based off of their prior week's steps. Based on the degree of functionality and design, the creation of an app can range from $8,000-$50,000, but even assuming the most expensive app possible, along with the download rate of MyFitnessPal, the total cost would equal ten cents a person (Thomas, 2014).

This systematic review supports the conclusion that smartphone apps are a usable, effective, and inexpensive patient weight loss intervention in the fight to decrease American obesity. This conclusion is tempered, however, by the small sample size and study limitations. Future studies need to further verify this conclusion by not only using more rigorous research methods, but also by helping others to categorize their apps for future comparisons. Suggestions for this include: 1) Using larger, more diverse samples, 2) Implementing better controls, 3) Identifying and committing to a behavioral science theory, and 4) Implementing and explaining how that theory influenced the creation of the app’s features. By meeting these suggestions, we can determine whether to invest more heavily in this technology, and if it is shown to be truly effective, we will hopefully be able to curb the rate of obesity in the United States.

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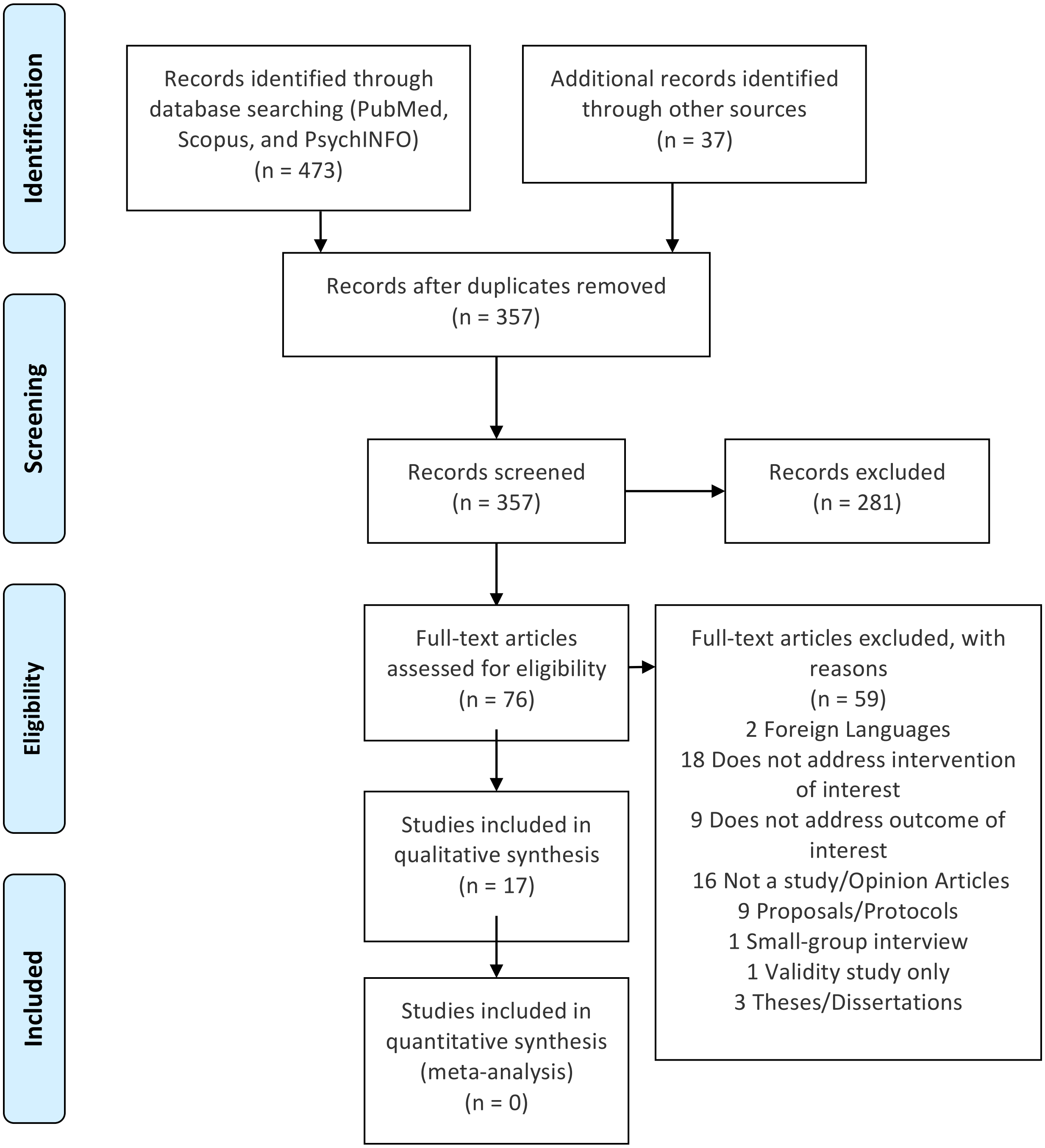

Figure 1. PRISMA Diagram showing the process of choosing articles for the literature review.

Table 1

Weight Loss Apps: General Study Characteristics

Lead Author	Mobile App	Key Features	Other Interventions	Comparison Group(s)	Behaviors Targeted	Theory Type	Theory Cited	Sample
(Carter et al., 2013)	My Meal Mate	• Set weight loss goals • Monitor daily caloric intake and energy expenditure • Meals linked with national food database • Tailored weekly text messages	None	• Self-monitoring slimming website • A food diary accompanied by a calorie-counting book	Diet/ Physical Activity	Analytic	None	N=128
(Hingle et al., 2013)	Twitter	• Hashtags representing food groups and reasons for eating (eg. #protein, #mood) • Option to embed contextual information using photos, text, and links	Training in how to record all food and beverages for three days	None	Diet	Social	Theory of Planned Behavior	N=50
(Donaire-Gonzalez et al., 2013)	CalFit	• Track physical activity intensity and duration	None	Actigraph GT3X	Physical Activity	Analytic	None	N=36
(Brindal et al., 2013)	Support App	• Meal calendar • Weight tracker • Log of tasks to be completed • Trophy room where unlocked rewards could be viewed • Static dietary information • Tailored prompting	Provided information about the Celebrity Slim Meal Replacement Program in addition to meal replacements	Control App	Diet/ Physical Activity	Analytic/ Affective	Theory of Planned Behavior	N=58

Lead Author	Mobile App	Key Features	Other Interventions	Comparison Group(s)	Behaviors Targeted	Theory Type	Theory Cited	Sample
(M. Kirwan et al., 2013)	iStepLog	• Input daily number of steps taken	None	Pre-modified iStepLog	Physical Activity	Analytic	Social Cognitive Theory	N=12
(Morwenna Kirwan et al., 2012)	iStepLog	• Input daily number of steps taken	10,000 Steps-supported pedometer	Subjects who could only access the iStepLog website	Physical Activity	Analytic	Social Cognitive Theory	N=200
(Robinson et al., 2013)	Attentive Eating App	• Snap picture of food prior to eating • See most recent picture after finishing meal, along with questions about consumption • Prior to next meal, can see slideshow of what's been eaten throughout the day	None	None	Diet	Affective	Behavior Change Wheel Framework	N=12
(Lee et al., 2010)	SmartDiet	• Diet planner providing personalized nutrition information for food and activity • Diet game providing a game-style learning tool about nutritional intake and exercise	None	None	Diet	Analytic/ Affective	None	N=36

Lead Author	Mobile App	Key Features	Other Interventions	Comparison Group(s)	Behaviors Targeted	Theory Type	Theory Cited	Sample
(King et al., 2013)	Analytic	• Personalized and quantified goal-setting and behavioral feedback • Problem-solving around barriers to behavior change • Informational tips or advice for behavior change	App to provide ‘‘just-in-time’’ feedback to users based on the national recommendations for physical activity	Social/Affect apps	Physical Activity	Analytic	Social Cognitive Theory Self-Regulatory principles of behavior change	N=23
	Social	• Real-time social normative feedback • Social support for behavior change • Interactions with, and modeling of behaviors by, similar others • Group-based competition and collaboration	App to provide ‘‘just-in-time’’ feedback to users based on the national recommendations for physical activity	Analytic/Affect apps	Physical Activity	Social	Social Influence Theory	N=22
	Affective	• The use of an avatar as a visual model corresponding to self-based performance to provide real-time feedback on progress • Game-like feedback and ‘‘jack-pot’’ rewards contingent upon reaching behavior change mile-stones	App to provide ‘‘just-in-time’’ feedback to users based on the national recommendations for physical activity	Analytic/Social apps	Physical Activity	Affective	Operant Conditioning Principles	N=23
(Khalil & Abdallah, 2013)	STEP UP	• View number of steps walked, distance traveled and calories burned • View walking history • View progress during the current week • View one’s team’s progress during the week	None	Base application without social component	Physical Activity	Social/ Analytic	Theory of Reasoned Action	N=8

Lead Author	Mobile App	Key Features	Other Interventions	Comparison Group(s)	Behaviors Targeted	Theory Type	Theory Cited	Sample
(Fukuoka et al., 2010)	Physical Activity Program	• Physical Activity Diary • Prompting	Pedometer	None	Physical Activity	Analytic	None	N=41
(Hebden et al., 2013)	mHealth programme	• Record behavior, including daily minutes of physical activities performed and daily/weekly servings of fruit and vegetables eaten • Instantaneous tailored motivational advice • Feedback in reference to population health guidelines	Actigraph accelerometer, booklet and session with a dietitian	Only received Actigraph accelerometer, booklet and session with a dietitian	Diet/ Physical Activity	Analytic	None	N=51
(Rodrigues et al., 2013)	SapoFit	• Monitor physical exercise and dietary intake and create a personal health record • Share this data with social networks	None	None	Diet/ Physical Activity	Social/ Analytic	None	N=106
(Mattila et al., 2013)	The Wellness Diary	• Manual self-monitoring of weight, steps, exercise, eating, sleep, stress, smoking, and alcohol consumption • Automatic graphical feedback based on the entries	Weight scales and a pedometer	Received standard occupational healthcare	Diet/ Physical Activity	Analytic	None	N=352
	Mobile Coach	• Manual entry of exercises • Graphical and numerical feedback along with a comparison of the user's progress in terms of set targets	Weight scales and a pedometer	Received standard occupational healthcare	Physical Activity	Analytic	None	N=352
	SelfRelax	• Audio-guided relaxation for short relaxation sessions • Tailored for duration, purpose, body position, and background sounds for a relaxation session • Choose specific relaxation techniques	Weight scales and a pedometer	Received standard occupational healthcare	Stress	Affective	None	N=352

Lead Author	Mobile App	Key Features	Other Interventions	Comparison Group(s)	Behaviors Targeted	Theory Type	Theory Cited	Sample
(Rollo et al., 2011)	Nutricam	• Record meal with a photograph and voice recording	Written food diary	None	Diet	Analytic	None	N=10
(Ahtinen et al., 2009)	The Wellness Diary	• Journal weight, exercise, steps, eating, stress level, sleep duration and quality, and tobacco and alcohol consumption, which are used to personalize the main view	Weight scales and a pedometer	None	Diet/ Physical Activity	Analytic	None	N=119
	Mobile Coach	• Automatically generate training plans based on personal goals • Adapt the training program based on the exercises actually performed • Provide graphical feedback of the workouts compared to the plan	Weight scales and a pedometer	None	Physical Activity	Analytic	None	N=119
	SelfRelax	• Mobile relaxation program based on purpose (sleep, stress, migraine, other pain, or general relaxation) duration, position, background sounds, and relaxation techniques	Weight scales and a pedometer	None	Stress	Affective	None	N=119
(Turner-McGrievy & Tate, 2011)	FatSecret's Calorie Counter Twitter	• Not given	Podcast	Received podcast and a book with calorie and fat amounts in food	Physical Activity	Analytic Social	None	N=96

Table 2

Weight Loss Apps: Usefulness and Usability Studies

Lead Author	Use of App	Satisfaction	Ease of Use	Convenience of Use
(Carter et al., 2013)	• Significant (p=.001) at 6 months with a mean of 92 days	• Significant (p=.05) At 6 months, with 63.2% of smartphone participants being satisfied or very satisfied	• Not significant	• Significant (p=.001) with 64.9% reporting that they found the smartphone convenient
(Hingle et al., 2013)	• Total of 773 tweets containing 2862 hashtags were recorded	• 36% described the use of Twitter to record diet and behavior as a positive experience.	• 73% rated Twitter as very easy to use	• N/A
(Donaire-Gonzalez et al., 2013)	• Significant (p<.001) difference between use: 22 hours for CalFit and 24 hours for Actigraph GT3X	• N/A	• N/A	• N/A
(Brindal et al., 2013)	• Not significant	• 91% would recommend the Support app to someone else if they were embarking on a meal replacement program. No one in the control group would recommend the Control app	• 73% found it extremely easy to complete the basic functions of the app	• N/A
(Morwenna Kirwan et al., 2012)	• Logging frequency declined significantly (p>.001) in the matched group compared with the intervention group	• 89% agreed or strongly agreed that they would like to continue using the iStepLog application	• 95% found it easy to navigate around the iStepLog application • 91% found it easy to enter and edit steps in the application	• 89% agreed it was convenient to use the iStepLog application

Lead Author	Use of App	Satisfaction	Ease of Use	Convenience of Use
(M. Kirwan et al., 2013)	• N/A	• N/A	• 55% decrease in time to complete tasks was significant (p=.042).	• Not significant, although the scores were high for both groups indicating a high level of usability.
(Robinson et al., 2013)	• Participants accessed the application an average of 5.7 times a day. • The mean number of eating and drinking episodes recorded each day was 2.7 .	• Mean score for intent to use in the future was 3.8/5	• Mean score for ease of use was 4.7/5	• Mean score for convenience was 3.3/5
(Lee et al., 2010)	• 75% used the system once a week and 8% used it every day.	• 58% intended to use it in the future and 8% intended to use it every day.	• 58% agreed that the system was easy to use and the contents were interesting.	• N/A
(King et al., 2013)	• N/A	• N/A	• 87% reported that they found the apps easy to use.	• 77% reported that the length of time needed to use the apps ‘‘was about right.’’
(Hebden et al., 2013)	• N/A	• N/A	• N/A	• 23% reported that the operating time was slow.
(Rodrigues et al., 2013)	• N/A	• Over 90% of participants agreed or strongly agreed that the platform had an attractive design and that the environment is user-friendly and intuitive.	• Over 90% of participants agreed or strongly agreed that the platform is very easy to use.	• 50% of users were unhappy with the application response time.

Lead Author	Use of App	Satisfaction	Ease of Use	Convenience of Use
(Mattila et al., 2013)	• Less than 30% of subjects continued using Web or mobile technologies throughout the study.	• 59% felt that the Wellness Diary motivated them to improve personal wellness at 3 months, compared with 83% for a pedometer.	• N/A	• N/A
(Ahtinen et al., 2009)	• 51% of SelfRelax users used it at least 5 times. • 25% of Mobile Coach users made at least one entry a week. • 94% percent used Wellness Diary, with the median number of entries being 76 (range: 1-677).	• Out of those who set weight control as their main goal, 78% stated that WD included appropriate functions for them. • Out of those who set exercise activity and fitness level as their primary target 43% stated that Mobile Coach included appropriate functions for them. • Out of those who named stress control as their primary goal, 36% said that SelfRelax included appropriate functions for them.	• 85% reported usage of the app was easy to learn.	• N/A
(Rollo et al., 2011)	• 50/355 items consumed and recorded by subjects using the written food diary were not recorded by the Nutricam app.	• 70% preferred the Nutricam method, while 30% preferred the written diary.	• 100% reported that the Nutricam app was easy to use.	• 60% reported that it took less time to use the Nutricam than to use a written diary. 20% reported that the duration was the same.

Table 3

Weight Loss Apps: Effectiveness Studies

Lead Author	Change in weight	Change in behavior
(Carter et al., 2013)	• Using an intention to treat analysis, weight change was significant at 6 months, when the smartphone group was compared to the website group (-3.3 kg, 95% CI -5.4 to 1.2), but not when the smartphone group was compared to the diary group ($p=.12$). • Using a sub-analysis for only those who completed the study, weight change was not significant ($p=.63$) between the groups at 6 months.	• N/A
(Brindal et al., 2013)	• Weight loss favored the intervention group, but was not significant ($p=.08$).	• Significant effect ($p<0.003$) of week of intervention on change in motivation • Significant ($p=.012$) increase in positive affect for the Support app group relative to the Control group over the 8 weeks • 95% of intervention group felt that the app helped them to stick to the diet to some extent compared to 9% for control app.
(Robinson et al., 2013)	• Mean weight loss was 1.5 kg • 50% of participants lost 1 kg or more, 33% lost less than 1 kg and 16% of participants gained between 0.1 and 0.4 kg.	• N/A
(Lee et al., 2010)	• The three body composition measures (fat mass, weight, and BMI) were significantly decreased ($p<.05$).	• No significant differences were noted between intervention and control groups in regard to exercise, irregular eating, eating when stressed, smoking, and drinking.

Lead Author	Change in weight	Change in behavior
(King et al., 2013)	• N/A	• Participants reported significant (p<0.0001) mean increases in weekly minutes of brisk walking across the 8-week intervention period. • Participants reported significant (p<0.0001) mean weekly increases in total moderate-to-vigorous physical activities. • Participants reported significant (p<0.02), decreases in the daily amount of discretionary time they spent sitting in front of the television.
(Khalil & Abdallah, 2013)	• N/A	• Although results were not significant (p>.05), there was a trend to walk more for both groups.
(Fukuoka et al., 2010)	• N/A	• Average daily total steps (p=.001) and aerobic steps (p<.001) both increased significantly across the three weeks • Average daily caloric expenditure increased significantly (p=.008)
(Hebden et al., 2013)	• No evidence of an effect of the intervention on body weight or on BMI was found.	• No effect of the intervention on physical activity outcomes was found. • No effect of the intervention on fruit or vegetable intake was found.
(Mattila et al., 2013)	• Measured weight change was a significant 2.9% decrease (95% CI -4.8 to -1.3).	• 51 respondents reported that they had increased their amount of exercise. • Measured average change in aerobic fitness (METmax) was a significant 0.53 (95% CI 0.32 to 0.74).
(Turner-McGrievy & Tate, 2011)	• The percentage of weight loss at 3 and 6 months did not differ between the groups.	• There were no significant differences between groups in energy expenditure or intake at 3 or 6 months. • Groups did not differ in changes in fat intake, self-efficacy (WEL score), or weight-related eating behaviors (EBI score) at 3 or 6 months.